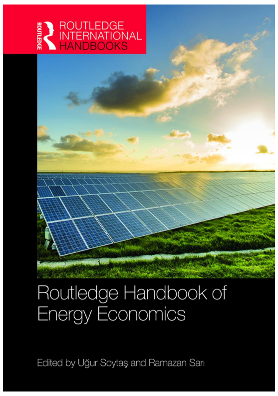

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Volatility spillovers on oil and forex markets

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Volatility spillovers on oil and forex markets

Jozef Baruník and Evžen Kočenda

1 Introduction

Volatility connectedness quantifies the dynamic and directional characterization of volatility spillovers among various assets or across markets (Diebold and Yilmaz, 2015).[1] The connectedness on financial markets is important to many areas of research, including risk management, portfolio allocation, and business cycle analysis. In this chapter we analyze connectedness between oil and forex markets. The reason for doing so is straightforward. Most of the crude oil production and sales is quoted and invoiced in US dollars. The massive amount of financial flows enters the forex market as the oil and oil-based commodities reach their destinations. Additional discussion on the channels through which the energy and foreign exchange markets may be linked was provided in Chapter 27. Hence, we hypothesize that volatility in oil prices transfers into the volatility of foreign currencies on the forex market and we analyze the extent of the associated connectedness.

Further, we extend our analysis to account for potential asymmetries in connectedness between the two markets. The asymmetries may materialize from a set of reasons. Oil is an asset where spillovers historically play a prominent role (Haigh and Holt, 2002). From the financial perspective, oil prices might be linked to large speculative trades (Hamilton, 2009; Caballero et al., 2008) and short run destabilization in oil prices may be caused by financial investors (Lombardi and Van Robays, 2011) due to oil's increasing financialization after 2001 (Fratzscher et al., 2013). Hence, asymmetries in connectedness might be a natural outcome. In this respect, currencies on the forex market would be able to continuously absorb or transfer those asymmetries because of the 24-hour operation of the global forex market with a huge information flow in terms of exchange rate quotes. Moreover, currencies are shown to exhibit asymmetric connectedness on its own (Baruník et al., 2017), which might be potentially transferred via the US dollar or other key currencies as the forex market exhibits a very high degree of integration, especially for key currencies (Kitamura, 2010).

Finally, we augment our analysis with studying the frequency dynamics of the connectedness. Baruník and Křehlík (2018) argue that shocks to economic activity impact variables at various frequencies with various strengths, and to understand the sources of connectedness in an economic system it is crucial to understand the frequency dynamics of the connectedness. The key reason rests in that agents operate on different investment horizons, represented by shorter or longer frequencies, because of the frequency-dependent formation of their preferences as shown in modeling strategies of Bandi and Tamoni (2017), Bansal and Yaron (2004), Cogley (2001), Ortu et al. (2013). In our analysis we consider the long-, medium-, and short-term frequency responses to shocks and analyze the financial connectedness at a desired frequency band.

In our analysis we proceed in the following way. We analyze connectedness between the two markets with the volatility spillover index (the DY index) of Diebold and Yilmaz (2009) that is based on forecast error variance decompositions from vector autoregressions (VARs). The methodology has been further improved in Diebold and Yilmaz (2012), who used a generalized VAR framework in which forecast-error variance decompositions are invariant to variable ordering. The DY index is a versatile measure allowing dynamic quantification of numerous aspects of volatility spillovers. In order to account for asymmetric sources of volatility we further compute the DY index with the realized semivariances introduced by Barndorff-Nielsen et al. (2010). The realized semivariances enable one to isolate and capture negative and positive shocks to volatility and thus are ideally suited to interpreting qualitative differences in volatility spillovers.[2]

Combination of the DY index and realized semivariances was introduced by Baruník et al. (2016) to measure asymmetries in volatility spillovers that are due to qualitatively different positive or negative returns. They produced a flexible measure allowing dynamic quantification of asymmetric connectedness. For a verbal interpretation of asymmetries we adopt the terminology established in the literature (Patton and Sheppard, 2015; Segal et al., 2015) that distinguishes asymmetries in spillovers originating due to qualitatively different uncertainty. Hence, we label spillovers as bad or good volatility spillovers (or negative or positive spillovers).

In addition to the total connectedness and asymmetric connectedness we also compute the frequency connectedness based on the approach of Baruník and Křehlík (2018). The frequency connectedness allows distinguishing extent of volatility spillovers among assets at various horizons. As such it allows to distinguish whether the connectedness is formed at shorter or longer frequencies.

The rest of the chapter is organized in the following way. In Section 2 we provide an overview of the literature related to volatility spillovers on the oil and forex markets. In Section 3 we formally introduce the methodological approach and formulate testable hypotheses. The data are described in Section 4. In three separate subsections of the Section 5 we present our results for total, asymmetric, and frequency connectedness. Finally, conclusions are offered in Section 6.

2 Literature review

Analyses of forex volatility spillovers based on the DY index are still infrequent. Diebold and Yilmaz (2015, Chapter 6), analyze the exchange rates of nine major currencies with respect to the US dollar from 1999 to mid-2013. They show that forex market connectedness increased only mildly after the 2007 financial crisis and the euro/US dollar exchange rate exhibits the highest volatility connectedness among all analyzed currencies. Greenwood-Nimmo et al. (2016) generalize the connectedness framework and analyze risk-return spillovers among the G10 currencies between 1999 and 2014. They find that spillover intensity is countercyclical and volatility spillovers across currencies increase during crisis times. Similarly, Bubák et al. (2011) document statistically significant intra-regional volatility spillovers among the European emerging foreign exchange markets and show that volatility spillovers tend to increase in periods characterized by market uncertainty, especially during the 2007–2008 financial crisis. Further, McMillan and Speight (2010) document the existence of volatility spillovers among the exchange rates of the US dollar, British pound, and Japanese yen with respect to the euro and show dominating effects coming from the US dollar. In addition, Antonakakis (2012) analyzes volatility spillovers among major currencies before and after the introduction of the euro and shows that the euro (Deutschmark) is the dominant net transmitter of volatility, while the British pound is the dominant net receiver of volatility in both periods. Finally, Baruník et al. (2017) document sizable volatility spillovers among the most actively traded currencies on the forex market. They also show that negative spillovers are chiefly tied to the dragging sovereign debt crisis in Europe while positive spillovers are correlated with the subprime crisis, different monetary policies among key world central banks, and developments on commodities markets.

There is also a segment of the literature that combines the assessment of volatility spillovers between the forex and stock markets. Grobys (2015) employ the DY index and finds very little evidence of volatility spillovers when markets are calm but a high level of total volatility spillovers following periods of economic turbulence. A similar conclusion is found by Do et al. (2015), who also emphasize that it is important to account for the volatility spillover information transmission especially during turbulent periods. Further, significant directional spillovers are identified between the forex and stock markets in several studies targeting developed and emerging markets (Do et al., 2016; Andreou et al., 2013; Kumar, 2013; Kanas, 2001) or specific countries or regions including the United States (Ito and Yamada, 2015), Japan (Jayasinghe and Tsui, 2008), China (Zhao, 2010), the Middle East, and North Africa (Arfaoui and Ben Rejeb, 2015). In addition, some studies analyze more complex interactions and volatility spillovers between the forex market and (1) stocks and bonds (Clements et al., 2015), (2) commodities (Salisu and Mobolaji, 2013), or (3) stocks, bonds, and commodities (Diebold and Yilmaz, 2009; Duncan and Kabundi, 2013; Aboura and Chevallier, 2014; Ghosh, 2014).

The research related to volatility spillovers among oil-based commodities is surprisingly limited. On weekly data, Haigh and Holt (2002) analyze the effectiveness of crude oil, heating oil, and unleaded gasoline futures in reducing price volatility for an energy trader: uncertainty is reduced significantly when volatility spillovers are considered in the hedging strategy. Using daily data for the period 1986–2001, Hammoudeh et al. (2003) analyzed the volatility spillovers of three major oil commodities (West Texas Intermediate, heating oil, and gasoline) along with the impact of different trading centers. Spillovers among various trading centers were also analyzed by Awartani and Maghyereh (2012), who investigated the dynamics of the return and volatility spillovers between oil and equities in the Gulf region. The spillover effect between the two major markets for crude oil (NYMEX and London's International Petroleum Exchange) has been studied by Lin and Tamvakis (2001), who found substantial spillover effects when both markets are trading simultaneously. More recently, Chang et al. (2010) have found volatility spillovers and asymmetric effects across four major oil markets: West Texas Intermediate (USA), Brent (North Sea), Dubai/Oman (Middle East), and Tapis (Asia-Pacific). Finally, Baruník et al. (2015) detect and quantify volatility spillovers among oil-based commodities: crude oil, gasoline, and heating oil. They also show asymmetries in that overall volatility spillovers due to negative (price) returns materialize to a greater degree than those due to positive returns and their occurrence correlates with low levels of crude oil inventories in the United States and often with world events that hamper crude oil supply. Negative spillovers thus frequently indicate the extent of real or potential crude oil unavailability.

To the best of our knowledge, there is no analysis of the connectedness between oil and forex markets, though.

3 Measuring asymmetric and frequency connectedness

Seminal papers by Diebold and Yilmaz (2009, 2012), along with other related studies, estimate volatility spillovers on daily (or weekly) high, low, opening, and closing prices. Estimators based on daily data offer, in general, good approximations of volatility. However, the low sampling frequency imposes some limitations. Having high-frequency data, we estimate volatility with convenient realized volatility estimators. Furthermore, to account for volatility spillover asymmetries, we follow Baruník et al. (2015, 2016), who use the realized semivariance framework of Barndorff-Nielsen et al. (2010), which offers an interesting possibility to decompose volatility spillovers due to negative and positive returns. The quantification of asymmetric volatility spillovers with realized semivariances was first employed in Baruník et al. (2015), where the authors define measures using two separate VAR systems for negative and positive semi-variances.

A natural way to describe the frequency dynamics (the long term, medium term, or short term) of the connectedness is to consider the spectral representation of variance decompositions based on frequency responses to shocks. Baruník and Křehlík (2018) introduced the general spectral representation of variance decompositions, and they show how we can use it to define the frequency-dependent connectedness measures.

In this section, we first introduce the two existing concepts of total and directional spillovers from Diebold and Yilmaz (2012), and then we describe a simple way to use realized semivariances in order to capture asymmetric volatility spillovers as well as frequency decomposition of the spillovers. In order to keep our description on a general level, we will label variables as assets.

3.1 Measuring volatility spillovers

The volatility spillover measure introduced by Diebold and Yilmaz (2009) is based on a forecast error variance decomposition from vector auto regressions (VARs). The forecast error variance decomposition traces how much of the H-step-ahead forecast error variance of a variable i is due to innovations in another variable j, thus it provides an intuitive way to measure volatility spillovers. For N assets, we consider an N-dimensional vector of realized volatilities, $\mathbf{RV_t} = (RV_{1t}, \dots, RV_{Nt})'$, to measure total volatility spillovers. In order to measure asymmetric volatility spillovers, we decompose daily volatility into negative (and positive) semivariances that provides a proxy for downside (and upside) risk. Using semivariances allows us to measure the spillovers from bad and good volatility and test whether they are transmitted in the same magnitude (Baruník et al., 2016). Thus, we consider $\mathbf{RV_t} = (RV_{1t}, \dots, RV_{nt})'$ to measure total volatility spillovers, and $\mathbf{RS_t^-} = \left(RS_{1t}^-, \dots, RS_{nt}^-\right)'$ and $\mathbf{RS_t^+} = \left(RS_{1t}^+, \dots, RS_{nt}^+\right)'$ to measure volatility spillovers due to negative and positive returns, respectively.

We start describing the procedure for the N-dimensional vector $\mathbf{RV_t} = (RV_{1t}, \dots, RV_{Nt})'$ and later extend the framework to accommodate realized semivariance. Let us model the N-dimensional vector $\mathbf{RV_t}$ by a weakly stationary vector autoregression VAR(p) as:

$$\mathbf{RV_t} = \sum_{i=1}^{p} \Phi_i \mathbf{RV}_{t-i} + \varepsilon_t, \tag{28.1}$$

where $\varepsilon_t \sim N(0, \Sigma_\varepsilon)$ is a vector of *iid* disturbances and $\mathbf{\Phi}_i$ denotes p coefficient matrices. For the invertible VAR process, the moving average representation has the following form:

$$\mathbf{RV_t} = \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t-i}. \tag{28.2}$$

The $N \times N$ matrices holding coefficients $\mathbf{\Psi}_i$ are obtained from the recursion $\Psi_i = \sum_{j=1}^{p} \Phi_j \Psi_{i-j}$, where $\mathbf{\Psi}_0 = \mathbf{I}_N$ and $\mathbf{\Psi}_i = 0$ for $i < 0$. The moving average representation is convenient for describing the VAR system's dynamics since it allows disentangling the forecast errors. These are further used for the computation of the forecast error variances of each variable in the system, which are attributable to various system shocks. However, the methodology has its limitations as it relies on the Cholesky factor identification of VARs. Thus, the resulting forecast variance decompositions can be dependent on variable ordering. Another important shortcoming is that it allows measuring total spillovers only. Therefore, Diebold and Yilmaz (2012) use the generalized VAR of Koop et al. (1996) and Pesaran and Shin (1998) to obtain forecast error variance decompositions that are invariant to variable ordering in the VAR model and it also explicitly includes the possibility to measure directional volatility spillovers.[3]

Total spillovers

In order to define the total spillover index of Diebold and Yilmaz (2012), we consider (1) the assets' own variance shares as fractions of the H-step-ahead error variances in forecasting the ith variable that are due to the assets' own shocks to i for $i = 1, \ldots, N$ and (2) the cross variance shares, or spillovers, as fractions of the H-step-ahead error variances in forecasting the ith variable that are due to shocks to the jth variable, for $i, j = 1, \ldots, N, i \neq j$. Then, the H-step-ahead generalized forecast error variance decomposition matrix Ω has the following elements for $H = 1, 2, \ldots$.

$$\omega_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\mathbf{e}_i' \Psi_h \Sigma_\varepsilon \mathbf{e}_j \right)^2}{\sum_{h=0}^{H-1} \left(\mathbf{e}_i' \Psi_h \Sigma_\varepsilon \Psi_h' \mathbf{e}_i \right)}, \quad i, j = 1, \ldots, N, \tag{28.3}$$

where $\mathbf{\Psi}_h$ are moving average coefficients from the forecast at time t; Σ_ε denotes the variance matrix for the error vector, ε_t; σ_{jj} is the jth diagonal element of Σ_ε; $\mathbf{e}_i$ and $\mathbf{e}_j$ are the selection vectors, with one as the ith or jth element and zero otherwise.

As the shocks are not necessarily orthogonal in the generalized VAR framework, the sum of the elements in each row of the variance decomposition table is not equal to one. Thus, we need to normalize each element by the row sum as:

$$\tilde{\omega}_{ij}^{H} = \frac{\omega_{ij}^{H}}{\sum_{j=1}^{N} \omega_{ij}^{H}}. \tag{28.4}$$

Diebold and Yilmaz (2012) then define the total spillover index as the contribution of spillovers from volatility shocks across variables in the system to the total forecast error variance, hence:

$$\mathcal{S}^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\omega}_{ij}^{H}. \tag{28.5}$$

Note that $\sum_{j=1}^{N} \tilde{\omega}_{ij}^{H} = 1$ and $\sum_{i,j=1}^{N} \tilde{\omega}_{ij}^{H} = N$. Hence, the contributions of spillovers from volatility shocks are normalized by the total forecast error variance. To capture the spillover dynamics, we use a 200-day rolling window running from point $t - 199$ to point t. Further, we set a forecast horizon $H = 10$ and a VAR lag length of 2.[4]

Directional spillovers

The total volatility spillover index indicates how shocks to volatility spill over all the assets. However, with the generalized VAR framework, we are able to identify directional spillovers using the normalized elements of the generalized variance decomposition matrix (Diebold and

Yilmaz, 2012). The directional spillovers are important, as they allow us to uncover the spillover transmission mechanism disentangling the total spillovers to those coming from or to a particular asset in the system.

Following Diebold and Yilmaz (2012) we measure the directional spillovers received by asset *i* from all other assets *j*:

$$\mathcal{S}^{H}_{N,i\leftarrow\bullet} = 100 \times \frac{1}{N}\sum_{\substack{j=1\\ i\neq j}}^{N} \tilde{\omega}^{H}_{ij}, \tag{28.6}$$

that is, we sum all numbers in rows *i*, except the terms on a diagonal that correspond to the impact of asset *i* on itself. The *N* in the subscript denotes the use of an *N*-dimensional VAR. Conversely, the directional spillovers transmitted by asset *i* to all other assets *j* can be measured as the sum of the numbers in the column for the specific asset, again except the diagonal term:

$$\mathcal{S}^{H}_{N,i\rightarrow\bullet} = 100 \times \frac{1}{N}\sum_{\substack{j=1\\ i\neq j}}^{N} \tilde{\omega}^{H}_{ij}. \tag{28.7}$$

As we now have complete quantification of how much an asset receives (transmits), denoted as the direction from (to), we can compute how much each asset contributes to the volatility in other assets in net terms. The net directional volatility spillover from asset *i* to all other assets *j* is defined as the difference between gross volatility shocks transmitted to and received from all other assets:

$$\mathcal{S}^{H}_{N,i} = \mathcal{S}^{H}_{N,i\rightarrow\bullet} - \mathcal{S}^{H}_{N,i\leftarrow\bullet}. \tag{28.8}$$

3.2 Measuring asymmetric spillovers

We now describe how to capture and measure asymmetries in volatility spillovers. Specifically, we are able to account for spillovers from volatility due to negative returns $\left(\mathcal{S}^{-}\right)$ and positive returns $\left(\mathcal{S}^{+}\right)$, as well as directional spillovers from volatility due to negative returns $\left(\mathcal{S}^{-}_{i\leftarrow\bullet}, \mathcal{S}^{-}_{i\rightarrow\bullet}\right)$, and positive returns $\left(\mathcal{S}^{+}_{i\leftarrow\bullet}, \mathcal{S}^{+}_{i\rightarrow\bullet}\right)$. Based on the previous exposition, to isolate asymmetric volatility spillovers we need to replace the vector of volatilities $\mathbf{RV_t} = (RV_{1t}, \ldots, RV_{nt})'$ defined in Equation (28.1) with the vector of negative semivariances $\mathrm{RV_t} = \left(RV_{1t}, \ldots, RV_{nt}\right)'$ or the vector of positive semivariances $\mathbf{RS^{-}_{t}} = \left(RS^{-}_{1t}, \ldots, RS^{-}_{nt}\right)'$. Note that in the above definitions we dropped the *H* index to ease the notational burden, but it remains a valid parameter for the estimation of spillover indices.

For the ease of exposition, we might also call the spillovers from bad and good volatility as negative and positive spillovers. Their quantification now enables testing several hypotheses. A comparison of the spillover values opens the following possibilities. If the contributions of RS^{-} and RS^{+} are equal, the spillovers are symmetric, and we expect the spillovers to be of the same magnitude as spillovers from *RV*. On the other hand, the differences in the realized semivariances result in asymmetric spillovers. These properties enable us to test the following hypotheses.

$$\mathcal{H}^{1}_{0}: \quad \mathcal{S}^{-} = \mathcal{S}^{+} \quad \text{against} \quad H_A: \quad \mathcal{S}^{-} \neq \mathcal{S}^{+}.$$

$$\mathcal{H}^{2}_{0}: \quad \mathcal{S}^{-}_{i\leftarrow\bullet} = \mathcal{S}^{+}_{i\leftarrow\bullet} \quad \text{against} \quad H_A: \quad \mathcal{S}^{-}_{i\leftarrow\bullet} \neq \mathcal{S}^{-}_{i\leftarrow\bullet}.$$

$$\mathcal{H}^{2}_{0}: \quad \mathcal{S}^{-}_{i\rightarrow\bullet} = \mathcal{S}^{+}_{i\rightarrow\bullet} \quad \text{against} \quad H_A: \quad \mathcal{S}^{-}_{i\rightarrow\bullet} \neq \mathcal{S}^{-}_{i\rightarrow\bullet}.$$

Rejecting a null hypothesis means that bad and good volatility does matter for spillover transmission in terms of magnitude as well as direction. Moreover, we assume that the values of the volatility spillover indices differ over time. To capture the time-varying nature, we compute the indices using a 200-day moving window that runs from point $t - 199$ to point t; more details are provided in Section 5.

Spillover asymmetry measure

In order to better quantify the extent of volatility spillovers, we introduce a spillover asymmetry measure. In case the negative and positive realized semivariance contribute to the total variation of returns in the same magnitudes, the spillovers from volatility due to negative returns $\left(S^-\right)$ and positive returns (S^+) will be equal to the spillovers from RV, and the null hypothesis $H_0^1 : S^- = S^+$ would not be rejected. This motivates a definition of the spillover asymmetry measure (SAM) simply as the difference between positive and negative spillovers:

$$SAM = S^+ - S^-, \tag{28.9}$$

where $\mathcal{S}^+$ and $\mathcal{S}^-$ are volatility spillover indices due to positive and negative semivariances, RS^+ and RS^-, respectively, with an H-step-ahead forecast at time t. $\mathcal{SAM}$ defines and illustrates the extent of asymmetry in spillovers due to RS^- and RS^+. When $\mathcal{SAM}$ takes the value of zero, spillovers coming from RS^- and RS^+ are equal. When $\mathcal{SAM}$ is positive, spillovers coming from RS^+ are larger than those from RS^- and the opposite is true when $\mathcal{SAM}$ is negative.

3.3 Frequency decompositions of connectedness measures

A natural way to describe the frequency dynamics (the long-term, medium-term, or short-term) of the connectedness is to consider the spectral representation of variance decompositions based on frequency responses to shocks instead of impulse responses to shocks. As a building block of the presented theory, we consider a frequency response function, $\mathbf{\Psi}(e^{-i\omega}) = \Sigma_h e^{-i\omega h} \mathbf{\Psi}_h$, which can be obtained as a Fourier transform of the coefficients $\mathbf{\Psi}_h$, with $i = \sqrt{-1}$. The spectral density of $\mathbf{RV_t}$ at frequency ω can then be conveniently defined as a Fourier transform of MA(∞) filtered series as

$$\boldsymbol{S}_{\mathbf{RV}}(\omega) = \sum_{h=-\infty}^{\infty} E\left(\mathbf{RV}_t \mathbf{RV}_{t-h}'\right) e^{-i\omega h} = \Psi\left(e^{-i\omega}\right) \Sigma \Psi'\left(e^{+i\omega}\right)$$

The power spectrum $\boldsymbol{S}_{\mathbf{RV}}(\omega)$ is a key quantity for understanding frequency dynamics, since it describes how the variance of the $\mathbf{RV}_t$ is distributed over the frequency components ω. Using the spectral representation for covariance, i.e. $E\left(\mathbf{R}V_t \mathbf{RV}_{t-h}'\right) = \int_{-\pi}^{\pi} S_x(\omega) e^{i\omega h} d\omega$, the following definition naturally introduces the frequency domain counterparts of variance decomposition.

While Baruník and Křehlík (2018) provide detailed derivation of the quantities, here we describe how to estimate the connectedness measures at different frequencies. The spectral quantities are estimated using standard discrete Fourier transforms. The cross-spectral density on the interval $d = (a, b) : a, b \in (-\pi, \pi), a < b$ is estimated as

$$\sum_{\omega} \hat{\Psi}(\omega) \hat{\Sigma} \hat{\Psi}'(\omega),$$

For $\omega \in \left\{ \left[\frac{aH}{2\pi} \right], \ldots, \left[\frac{bH}{2\pi} \right] \right\}$ where

$$\hat{\Psi}(\omega) = \sum_{h=0}^{H-1} \hat{\Psi}_h e^{-2i\pi\omega/H},$$

and $\hat{\Sigma} = \hat{\varepsilon}'\hat{\varepsilon} / (T - z)$, where z is a correction for a loss of degrees of freedom, and it depends on the VAR specification.

The decomposition of the impulse response function at the given frequency band is then estimated as $\hat{\Psi}(d) = \sum_{\omega} \hat{\Psi}(\omega)$. Finally, the generalized variance decompositions at a desired frequency band are estimated as

$$\left(\hat{\boldsymbol{\theta}}_d\right)_{j,k} = \sum_{\omega} \hat{\Gamma}_j(\omega)(\hat{\mathbf{f}}(\omega))_{j,k},$$

where

$$(\hat{f}(\omega))_{j,k} \equiv \frac{\hat{\sigma}_{kk}^{-1}\left((\hat{\Psi}(\omega)\hat{\Sigma})_{j,k}\right)^2}{\left(\hat{\Psi}(\omega)\hat{\Sigma}\hat{\Psi}'(\omega)\right)_{j,j}}$$

is estimated generalized causation spectrum, and

$$\hat{\Gamma}_j(\omega) = \frac{\left(\hat{\Psi}(\omega)\hat{\Sigma}\hat{\Psi}'(\omega)\right)_{j,j}}{(\Omega)_{j,j}},$$

is estimate of the weighting function, where $\Omega = \sum_{\omega} \hat{\Psi}(\omega)\hat{\Sigma}\hat{\Psi}'(\omega)$.

Then, the connectedness measures at a given frequency band of interest can be readily derived by plugging the $\left(\hat{\theta}_d\right)_{j,k}$ estimate into the traditional measures outlined above.[5]

4 Data

In this paper we compute volatility spillover measures on the foreign exchange futures contracts of six currencies and crude oil over the period 2 January 2007 to 12 February 2014. We use five-minute intraday prices of futures contracts that are automatically rolled over to provide continuous price records. The intraday returns are computed from log prices. The currencies are the Australian dollar (AUD), Canadian dollar (CAD), British pound (GBP), euro (EUR), Japanese yen (JPY), and Swiss franc (CHF).[6] All these currency contracts are quoted against the US dollar (i.e. one unit of a currency in terms of the US dollar). This is a typical approach in the forex literature (any potential domestic (US) shocks are integrated into all currency contracts). The currencies under research constitute a group of the most actively traded currencies globally (BIS, 2013; Antonakakis, 2012) and this is the reason for our choice: we aim to analyze asymmetric connectedness among the currencies that constitute two-thirds of the global forex turnover by currency pair (BIS, 2013); we do not pursue assessment of less traded currencies at the moment.

The foreign exchange, and crude oil futures contracts are traded on the Chicago Mercantile Exchange (CME) on a nearly 24-hour basis and transactions are recorded in Chicago time (CST). Trading activity starts at 5:00 p.m. CST and ends at 4:00 p.m. CST. To exclude potential jumps due to the one-hour gap in trading, we redefine the day in accordance with the electronic trading system. Furthermore, we eliminate transactions executed on Saturdays, Sundays, US federal holidays, 24–26 December and 31 December–2 January, because of the low activity on these days, which could lead to estimation bias. The data are available from Tick Data, Inc.[7]

5 Results: total, asymmetric, and frequency connectedness

5.1 Total connectedness

In Figure 28.1, we present the total connectedness among the six currencies (solid line) along with the total connectedness among the currencies and the oil (solid bold line). The total volatility spillovers measure is calculated based on Diebold and Yilmaz (2012). First we examine the connectedness on the forex market (solid line): the connectedness is quite high during the GFC period until 2010 and then in 2012 and early 2014. The total connectedness values of 65% and above during the 2008–2010 period are comparable to those found in Diebold and Yilmaz (2015). The plot exhibits a distinctive structural change in total connectedness among the six currencies under research: an initial high connectedness is interrupted by a short drop during 2009 and decreases gradually after 2010 but then in 2013 begins to rise. The period is marked by two distinctive phenomena. One is the difference between monetary policies among the Fed, ECB, and Bank of Japan. While the Fed stopped the quantitative easing (QE) policy in 2014, the ECB was beginning to pursue it and the Bank of Japan was already active in pursuing this policy. From 2013 the policy differences affected the capital flows and carry-trade operations so that the US dollar began to appreciate against the euro and yen. At the same time, falling commodity prices exerted downward pressure on inflation and interest rates. This course affects most of the currencies in our sample as commodities are quoted in vehicle currencies (USD, EUR, JPY) and interest rate cuts occurred for commodity currencies (AUD, CAD), diminishing their appeal for carry-trade activities. Hence, the increased volatility and spillovers among currencies from 2013 on are to be found in combined effects chiefly rooted in monetary steps.

Second, from Figure 28.1 we can further gauge information on the total connectedness among the currencies and the crude oil (solid bold line). By adding crude oil into the set of

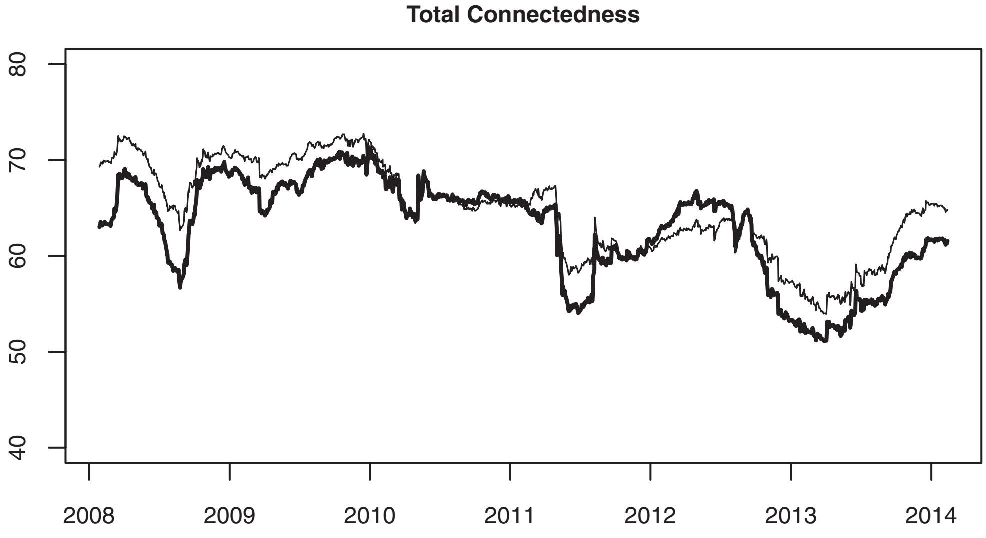

Figure 28.1 The total volatility spillovers of six currencies (solid line), the total volatility spillovers of six currencies and crude oil (bold solid line)

currencies we can imagine that we create a forex portfolio into which a crude oil is added. Gradual financialization of the crude oil makes the computation of the total connectedness a realistic exercise. A general observation is that by combining crude oil with the set of currencies a total connectedness of a hypothetical portfolio is lower over the observed time span than the total connectedness of the portfolio composed solely from the currencies. The only exception is a period in 2012 when average crude oil prices were at historically high levels. Such crude oil price development is behind the increase in the total volatility spillovers in a hypothetical portfolio.

We can further enrich our observations from the Figure 28.1 by quantifying directional spillovers among the analyzed assets. Following Diebold and Yilmaz (2012), we compute directional spillovers and show how volatility from a specific currency transmits to other currencies in our sample ("contribution TO"). Similarly we are also able to show the opposite link of the extent of spillovers going from other currencies to a specific currency ("contribution FROM"). The condensed information on the extent of such directional spillovers is presented in Table 28.1 – in aggregate form we show how specific currencies transmit and receive spillovers, or in other words how the shocks into one currency impact other currencies. The highest values lie on a diagonal and they represent the extent of how own volatility of a specific currency affects its own subsequent volatility. Other values in the matrix show the volatility spillover impact between currency pairs. An interesting and intuitive observation is that shocks to each of the two commodity currencies (AUD and CAD) impact these currencies to larger extent that the rest of currencies. Similarly, the euro and British pound do spill a great portion of their volatilities between each other. Finally, the Swiss franc and Japanese yen seem to be the calmest currencies in the portfolio as their volatility impact on each other as well as with respect to other currencies is rather low and indirectly supports their status of safe havens.

In Table 28.2 we add the crude oil to the portfolio and present the bilateral volatility impacts among the assets in a similar manner as in Table 28.1. By looking at the matrix, we observe that crude oil's own volatility dominates this asset and that pattern of volatility spillovers among the currencies remains same as that observed in Table 28.1. However, we obtain additional insights on volatility spillovers between crude oil and currencies. An important general observation is that shocks to the crude oil transfer to currencies in lesser extent than how the shocks to currencies spill over to the crude oil. And of course, there are some interesting details. First, volatility transfer from crude oil to the Japanese yen and Swiss franc seems to be quite balanced as it travels other way around. The two safe haven currencies seem to be resistant to the shocks into the crude oil and reluctant to transfer their volatilities to the oil as well. Second, shocks from the two commodity currencies (AUD and CAD) affect the crude oil to much greater extent than those from the rest of currencies. We conjecture that, despite its ongoing financialization, the crude oil is primarily a commodity and its link to other commodities that Australia and Canada export might be the reason for such degree of mutual extent of volatility spillovers.

Table 28.1 Volatility connectedness table without crude oil

	AUD	*GBP*	*CAD*	*EUR*	*JPY*	*CHF*	*FROM*
AUD	35.16	16.62	16.48	13.71	9.10	8.93	10.81
GBP	17.16	32.38	13.42	18.02	8.07	10.95	11.27
CAD	21.00	16.95	34.03	12.06	7.25	8.71	11.00
EUR	15.04	20.00	10.55	30.95	6.05	17.40	11.51
JPY	14.92	16.89	8.75	10.97	37.67	10.80	10.39
CHF	13.21	15.82	10.57	22.88	7.86	29.66	11.72
TO	13.56	14.38	9.96	12.94	6.39	9.47	66.69

Table 28.2 Volatility connectedness table with crude oil

	Crude Oil	*AUD*	*GBP*	*CAD*	*EUR*	*JPY*	*CHF*	*FROM*
Crude Oil	48.43	12.07	11.02	13.24	7.12	3.81	4.31	7.37
AUD	6.50	33.45	15.36	15.17	12.76	8.60	8.16	9.51
GBP	6.64	16.18	30.60	12.07	16.88	7.64	9.99	9.91
CAD	9.00	19.58	15.07	31.25	10.84	6.72	7.54	9.82
EUR	4.91	14.36	18.90	9.72	29.82	5.80	16.49	10.03
JPY	3.89	14.34	16.05	8.17	10.46	36.83	10.26	9.02
CHF	4.89	12.58	14.80	9.61	21.93	7.59	28.61	10.20
TO	5.12	12.73	13.03	9.71	11.43	5.74	8.11	65.86

5.2 Asymmetric connectedness

So far we have shown evidence based on spillovers that did not account for asymmetries. Now, we will employ the realized semivariances to separate qualitatively different shocks to volatility. Realized measures are defined on a continuous-time stochastic process of log-prices, p_t, evolving over a time horizon $(0 \leq t \leq T)$. The process consists of a continuous component and a pure jump component,

$$p_t = \int_0^t \mu_s ds + \int_0^t \sigma_s dW_s + J_t \,, \tag{28.10}$$

where μ denotes a locally bounded predictable drift process, σ is a strictly positive volatility process, and J_t is the jump part, and all is adapted to some common filtration F. The quadratic variation of the log prices p_t is:

$$[p_t, p_t] = \int_0^t \sigma_s^2 ds + \sum_{0<s\leq t} (\Delta p_s)^2, \tag{28.11}$$

where $\Delta p_s = p_s - p_{s-}$ are jumps, if present. The first component of Equation (28.11) is integrated variance, whereas the second term denotes jump variation. Andersen and Bollerslev (1998) proposed estimating quadratic variation as the sum of squared returns and coined the name "realized variance" (RV). The estimator is consistent under the assumption of zero noise contamination in the price process.

Let us denote the intraday returns $r_k = p_k - p_{k-1}$, defined as a difference between intraday equally spaced log prices $p_0, \ldots, p_n$ over the interval $[0, t]$, then

$$RV = \sum_{k=1}^{n} r_k^2 \tag{28.12}$$

converges in probability to $[p_t, p_t]$ with $n \to \infty$.

Barndorff-Nielsen et al. (2010) decomposed the realized variance into realized semivariances (RS) that capture the variation due to negative (RS^-) or positive (RS^+) price movements (e.g. bad and good volatility). The realized semivariances are defined as:

$$RS^- = \sum_{k=1}^{n} \mathbb{I}(r_k < 0) r_k^2, \tag{28.13}$$

$$RS^+ = \sum_{k=1}^{n} \mathbb{I}(r_k \geq 0) r_k^2. \tag{28.14}$$

Realized semivariance provides a complete decomposition of the realized variance, hence:

$$RV = RS^{-} + RS^{+}. \tag{28.15}$$

The limiting behavior of realized semivariance converges to $1/2\int_0^t \sigma_s^2 ds$ plus the sum of the jumps due to negative and positive returns (Barndorff-Nielsen et al., 2010). The negative and positive semivariance can serve as a measure of downside and upside risk as it provides information about variation associated with movements in the tails of the underlying variable.

In short, negative realized semivariance (RS^{-}) isolates negative shocks to volatility or, in other words, RS^{-} allows capturing volatility due to negative changes (returns) in exchange rates and the crude oil. The opposite is true for positive realized semivariance (RS^{+}).

In Figure 28.2 we plot the dynamics of the spillover asymmetry measure (SAM) computed as the difference between the spillover indices for all six currencies (solid line) plus six currencies and the crude oil (solid bold line) where inputs are realized semivariances. The volatility associated with negative (positive) innovations to returns has been termed as bad (good) volatility (Patton and Sheppard, 2015; Segal et al., 2015). We follow this terminology and label spillovers in Figure 28.2 as bad and good volatility spillovers (or simply negative and positive spillovers).

The plot of SAM in Figure 28.2 exhibits a different pattern than that of the total connectedness measure in Figure 28.1. It provides a qualitatively new picture. When a solid line lies in a positive domain, it is a sign that asymmetries due to positive shocks measured with RS^{+} dominate asymmetries due to the negative shocks. On the other hand, asymmetries due to negative shocks measured with the RS^{-} dominate when solid lines is situated in the negative domain.

A general observation from Figure 28.2 is that inclusion of the crude oil into the forex portfolio tends to increase dominance of the asymmetries due to positive spillovers. The pattern is most clearly visible over the time span from 2010 onwards. There is an exception, though. Shortly after the global financial crisis in 2009, inclusion of the crude oil correlates with non-negligible

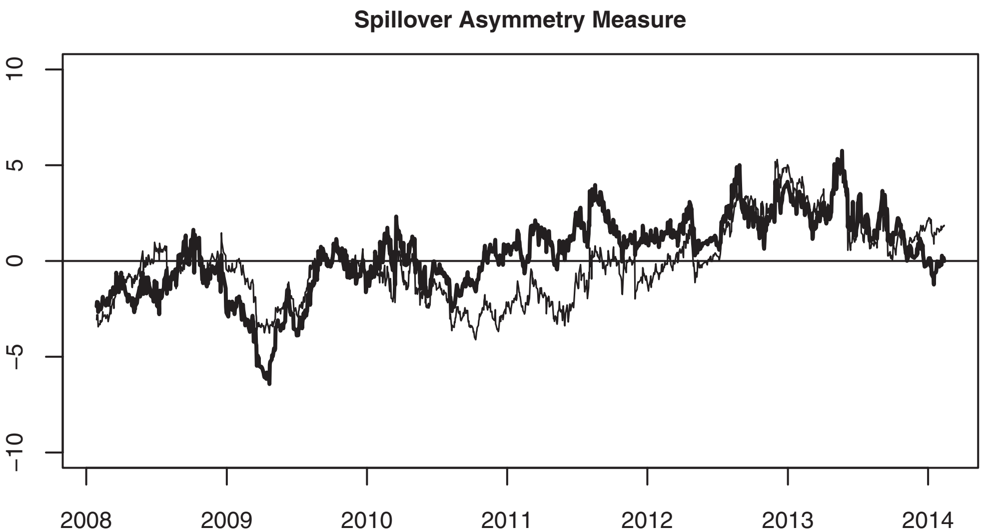

Figure 28.2 Spillover asymmetry measure (SAM). Solid line represents the SAM for the forex market only, while the solid bold line represents the SAM for the forex market with crude oil.

increase of the negative spillovers. This excess is underlined by an intuitive explanation. Plummeting oil prices at the end of 2008 and beginning of 2009 represent strong negative shocks that are behind the sharp increase of negative spillovers. Further developments from the end of 2009 onwards reflect rising prices and the progressive financialization of commodities (Cheng and Xiong, 2013).

Based on the plot of the SAM in Figure 28.2 we conclude that bad volatility spillovers dominate good volatility spillovers for the forex portfolio during much of the analyzed period. However, when crude oil is added into the hypothetical portfolio the dominance reverses in favor of the positive spillovers.

5.3 Frequency connectedness

In Figure 28.3 we present plots of the frequency connectedness that are computed based on Baruník and Křehlík (2018). The frequency connectedness is computed for the complete portfolio of six currencies and the crude oil. Three lines represent extent of connectedness at three horizons. Short-term horizon is represented by a simple solid line, while the medium bold line captures the medium-term horizon. Long-run connectedness is portrayed with the bold line. Short-term and medium-term connectedness share relatively similar dynamic path that begins to diverge only in 2013. Short-term and medium-term connectedness is also quite low. On the other hand long-run connectedness is rather detached from the other two frequencies. Long-run connectedness is also somewhat higher most of the time. The pattern indicates that connectedness is formed predominantly at long frequencies. This means that shocks have long-term impact and that short- and medium-term impact is rather limited.

The long-term connectedness reaches highest values during the global financial crisis and well into 2010. The long-term connectedness can be seen rising again in 2012. The outburst of

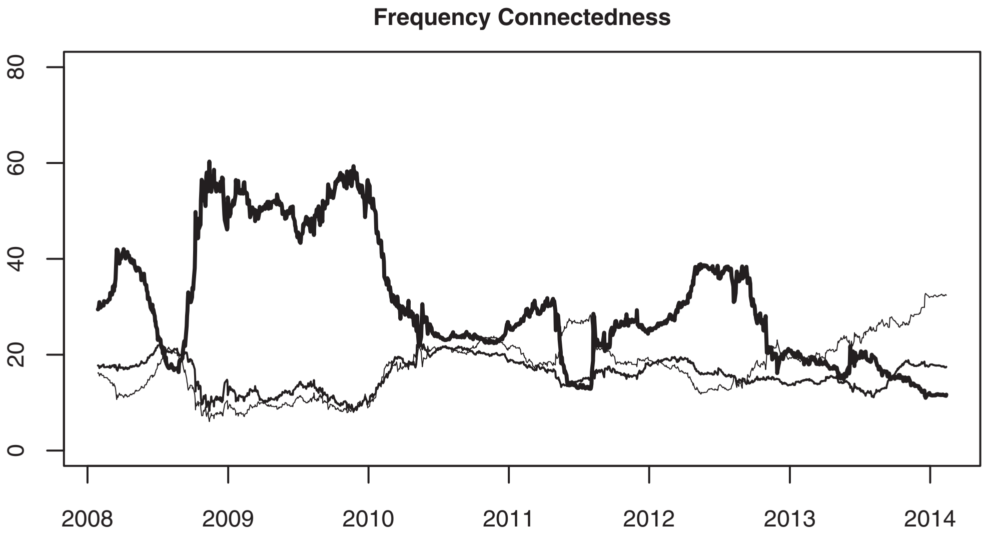

Figure 28.3 Dynamic frequency connectedness. The frequency connectedness at short-term horizon defined at $d_1 \in [1, 5]$ days in solid line, medium-term horizon defined at $d_2 \in (5, 20]$ days medium bold line, and long-term horizon defined at $d_3 \in (20, 300]$ days in bold line. Note that all lines through the frequency bands d_s sum to the total connectedness.

the long-term connectedness are related to financial crisis and then to the European sovereign debt crisis in 2012. Unlike short- and medium-term connectedness, the long-run connectedness seems to be quite sensitive to heightened uncertainty on the market. The sharp differences in the long-term and shorter-term connectedness should be attributed to the differences in how investors perceive the stability of the economic and financial system. High uncertainty on the market and the belief that the economic situation reflects deeper and systemic imbalances is mirrored in high long-term connectedness during the periods in which the shocks are transmitted through the system with high persistence. Finally, one should also note that a simple sum of the three lines provides the total connectedness plotted earlier in Figure 28.1.

6 Conclusion

We analyze total, asymmetric, and frequency connectedness on the oil and forex markets using high-frequency intraday data over 2007–2015. Methodologically, we compute the volatility spillover index of Diebold and Yilmaz (2012) to analyze total connectedness. Further, we use the procedure of Baruník et al. (2016) to quantify asymmetric connectedness that is due to bad and good volatility (proxied by negative and positive returns). Finally, we assess the extent of the frequency connectedness based on the approach of Baruník and Křehlík (2018). Our key results can be summarized as follows.

First, a general observation is that by combining crude oil with the set of currencies a total connectedness of the oil and forex markets over the researched period is lower than the total connectedness of the forex market itself. The year 2012 represents a single exception because of historically high oil prices associated with their higher volatility.

Second, in terms of asymmetries we show that bad volatility dominates connectedness on the forex market during much of the analyzed period. However, when we measure connectedness on both oil and forex markets the dominance reverses in favor of the good volatility.

Third, the frequency connectedness analysis reveals that dynamic of the shorter and longer term connectedness dramatically differs. While shorter-term connectedness is usually low over the whole researched period, the long-term connectedness sharply rises during the global financial crisis and European debt crisis.

Our approach brings qualitatively new insights as it provides the detailed and multifaceted evidence on the dynamics of the connectedness on two important markets. Our analysis also provides some direct implications. Specifically, we show that extent of volatility spillovers dampens when both oil and forex markets are assessed jointly. Further, our results imply that adding oil into a hypothetical portfolio of oil and foreign currencies alters asymmetry in connectedness between the two classes of assets. Finally, we show that the long-term connectedness reflects worrisome beliefs of investors and can serve as a sensitive indication of the heightened market uncertainty.

Notes

1 In the text, we use the terms "connectedness" and "spillovers" interchangeably, as both terms have been used in the literature to describe the same phenomenon.
2 The realized semivariances were quickly adopted in several recent contributions, see e.g. Feunou et al. (2013), Patton and Sheppard (2015), and Segal et al. (2015).
3 The generalized VAR allows for correlated shocks, hence the shocks to each variable are not orthogonalized.
4 In addition, we constructed the spillover index with rolling windows of 150 and 100 days to check the robustness of our results. We have also experimented with different H values and we find that the results do not materially change and are robust with respect to the window and horizon selection. The VAR lag length was chosen based on AIC to produce the most parsimonious model.

5 The entire estimation is done using the package frequencyConnectedness in R software. The package is available on CRAN or on https://github.com/tomaskrehlik/frequencyConnectedness.

6 The Australian dollar and Canadian dollar are two commodity currencies in our sample. A commodity currency refers to some currencies that co-move with the world prices of primary commodity products as the specific raw materials constitute a non-negligible part of the GDP in countries where the commodity currency is used as a legal tender. Most of these countries are typically developing countries. However, the group also includes developed countries like Canada and Australia. In the foreign exchange market, commodity currencies generally refer not only to the Australian dollar, Canadian dollar, and New Zealand dollar (see Chen and Rogoff (2003) for a detailed analysis), but also to the Norwegian krone, South African rand, Brazilian real, Russian ruble, and Chilean peso.

7 www.tickdata.com/.

References

Aboura, S. and J. Chevallier (2014). Cross-market spillovers with 'volatility surprise'. *Review of Financial Economics 23*(4), 194–207.

Andersen, T. G. and T. Bollerslev (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*, 885–905.

Andreou, E., M. Matsi, and A. Savvides (2013). Stock and foreign exchange market linkages in emerging economies. *Journal of International Financial Markets, Institutions and Money 27*, 248–268.

Antonakakis, N. (2012). Exchange return co-movements and volatility spillovers before and after the introduction of euro. *Journal of International Financial Markets, Institutions and Money 22*(5), 1091–1109.

Arfaoui, M. and A. Ben Rejeb (2015). Return dynamics and volatility spillovers between FOREX and stock markets in MENA countries: What to remember for portfolio choice? *International Journal of Management and Economics 46*(1), 72–100.

Awartani, B. and A. I. Maghyereh (2012). Dynamic spillovers between oil and stock markets in the gulf cooperation council countries. *Energy Economics 36*, 28–42.

Bandi, F. M. and A. Tamoni (2017). *The horizon of systematic risk: A new beta representation*, unpublished manuscript.

Bansal, R. and A. Yaron (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *The Journal of Finance 59*(4), 1481–1509.

Barndorff-Nielsen, O., S. Kinnebrock, and N. Shephard (2010). *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle*, Chapter Measuring Downside Risk-Realised Semivariance. Oxford: Oxford University Press.

Baruník, J., E. Kočenda, and L. Vácha (2015). Volatility spillovers across petroleum markets. *Energy Journal 36*(3), 309–329.

Baruník, J., E. Kočenda, and L. Vácha (2016). Asymmetric connectedness on the US stock market: Bad and good volatility spillovers. *Journal of Financial Markets 27*, 55–78.

Baruník, J., E. Kočenda, and L. Vácha (2017). Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance 77*, 39–56.

Baruník, J. and T. Křehlík (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics forthcoming*.

BIS (2013). Triennial central bank survey foreign exchange turnover in April 2013: Preliminary global results. Technical report, Monetary and Economic Department, Bank for International Settlements.

Bubák, V., E. Kočenda, and F. Žikeš (2011). Volatility transmission in emerging European foreign exchange markets. *Journal of Banking & Finance 35*(11), 2829–2841.

Caballero, R. J., E. Farhi, and P.-O. Gourinchas (2008). Financial crash, commodity prices and global imbalances. Technical report, National Bureau of Economic Research.

Chang, C.-L., M. McAleer, and R. Tansuchat (2010). Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets. *Energy Economics 32*(6), 1445–1455.

Chen, Y.-C. and K. Rogoff (2003). Commodity currencies. *Journal of International Economics 60*(1), 133–160.

Cheng, I.-H. and W. Xiong (2013). The financialization of commodity markets. *Annual Review of Financial Economics (First published online as a review in advance on October 09, 2014 DOI: 10.1146/annurev-financial-110613-034432) 6*, 419–441.

Clements, A. E., A. S. Hurn, and V. V. Volkov (2015). Volatility transmission in global financial markets. *Journal of Empirical Finance 32*, 3–18.

Cogley, T. (2001). A frequency decomposition of approximation errors in stochastic discount factor models. *International Economic Review 42*(2), 473–503.

Diebold, F. X. and K. Yilmaz (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal 119*(534), 158–171.

Diebold, F. X. and K. Yilmaz (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting 28*(1), 57–66.

Diebold, F. X. and K. Yilmaz (2015). *Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring*. Oxford: Oxford University Press.

Do, H. X., R. Brooks, and S. Treepongkaruna (2015). Realized spill-over effects between stock and foreign exchange market: Evidence from regional analysis. *Global Finance Journal 28*, 24–37.

Do, H. X., R. Brooks, S. Treepongkaruna, and E. Wu (2016). Stock and currency market linkages: New evidence from realized spillovers in higher moments. *International Review of Economics & Finance 42*, 167–185.

Duncan, A. S. and A. Kabundi (2013). Domestic and foreign sources of volatility spillover to South African asset classes. *Economic Modelling 31*, 566–573.

Feunou, B., M. R. Jahan-Parvar, and R. Tédongap (2013). Modeling market downside volatility. *Review of Finance 17*(1), 443–481.

Fratzscher, M., D. Schneider, and I. Van Robays (2013). Oil prices, exchange rates and asset prices. (no. 1302). Technical report, Discussion Papers, DIW Berlin.

Ghosh, S. (2014). Volatility spillover in the foreign exchange market: The Indian experience. *Macroeconomics and Finance in Emerging Market Economies* 7(1), 175–194.

Greenwood-Nimmo, M. J., V. H. Nguyen, and B. Rafferty (2016). Risk and return spillovers among the G10 currencies. *Journal of Financial Markets forthcoming*.

Grobys, K. (2015). Are volatility spillovers between currency and equity market driven by economic states? Evidence from the US economy. *Economics Letters 127*, 72–75.

Haigh, M. S. and M. T. Holt (2002). Crack spread hedging: Accounting for timevarying volatility spillovers in the energy futures markets. *Journal of Applied Econometrics 17*(3), 269–289.

Hamilton, J. D. (2009). Understanding crude oil prices. *The Energy Journal 30*(2), 179–206.

Hammoudeh, S., H. Li, and B. Jeon (2003). Causality and volatility spillovers among petroleum prices of WTI, gasoline and heating oil in different locations. *The North American Journal of Economics and Finance 14*(1), 89–114.

Ito, T. and M. Yamada (2015). High-frequency, algorithmic spillovers between nasdaq and forex. Technical report, National Bureau of Economic Research.

Jayasinghe, P. and A. K. Tsui (2008). Exchange rate exposure of sectoral returns and volatilities: Evidence from Japanese industrial sectors. *Japan and the World Economy 20*(4), 639–660.

Kanas, A. (2001). Volatility spillovers between stock returns and exchange rate changes: International evidence. *Journal of Business Finance & Accounting 27*(3), 447–465.

Kitamura, Y. (2010). Testing for intraday interdependence and volatility spillover among the Euro, the pound and the Swiss franc markets. *Research in International Business and Finance 24*(2), 158–171.

Koop, G., M. H. Pesaran, and S. M. Potter (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics 74*(1), 119–147.

Kumar, M. (2013). Returns and volatility spillover between stock prices and exchange rates: Empirical evidence from IBSA countries. *International Journal of Emerging Markets 8*(2), 108–128.

Lin, S. X. and M. N. Tamvakis (2001). Spillover effects in energy futures markets. *Energy Economics 23*(1), 43–56.

Lombardi, M. J. and I. Van Robays (2011). Do financial investors destabilize the oil price? European Central Bank, Working Paper No.1346.

McMillan, D. G. and A. E. Speight (2010). Return and volatility spillovers in three euro exchange rates. *Journal of Economics and Business 62*(2), 79–93.

Ortu, F., A. Tamoni, and C. Tebaldi (2013). Long-run risk and the persistence of consumption shocks. *Review of Financial Studies 26*(11), 2876–2915.

Patton, A. J. and K. Sheppard (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *The Review of Economics and Statistics 97*(3), 683–697.

Pesaran, H. H. and Y. Shin (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters 58*(1), 17–29.

Salisu, A. A. and H. Mobolaji (2013). Modeling returns and volatility transmission between oil price and US-Nigeria exchange rate. *Energy Economics 39*, 169–176.

Segal, G., I. Shaliastovich, and A. Yaron (2015). Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics 117*(2), 369–397.

Zhao, H. (2010). Dynamic relationship between exchange rate and stock price: Evidence from China. *Research in International Business and Finance 24*(2), 103–112.